

# **A new method in diffraction tomography based on the optimization of a topology**

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# Outline

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Introduction: Inverse scattering problem

First method: Shape optimization

Reconstructions

An improved method: Topological derivative

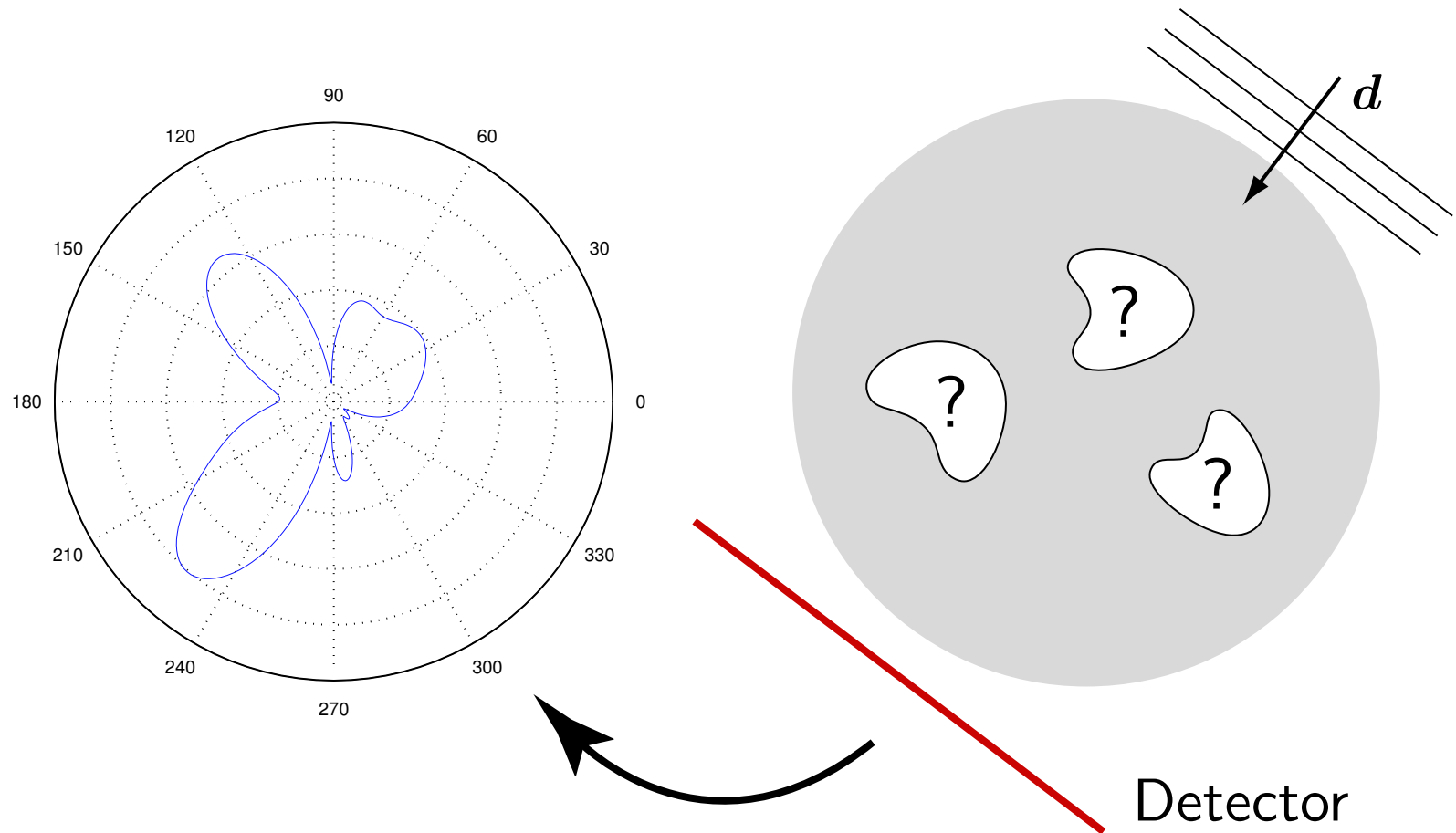
Reconstructions

Conclusions and future work

# Introduction: Inverse scattering problem

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Reconstruct shape of scatterer(s)



# Introduction: Inverse scattering problem

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**Problem definition:** Given

- the measured signal  $u_m$  on  $\Gamma_s$ ,
- the forward model  $a(\Omega; w, u) = \ell(\Omega; w) \ \forall w$ ,
- the operator  $\mathcal{F}(\Omega, u(\Omega)) = u_{\text{sp}}$  on  $\Gamma_s$ ,

find the domain  $\Omega$  such that “ $\mathcal{F}(\Omega, u(\Omega)) = u_T$ .”

**Remarks:**

- $\Omega$  is the domain where the model is valid.
- $a(\Omega; w, u) = \ell(\Omega; w) \ \forall w$  describes the interaction between the incident wave and the medium.

# Introduction: Inverse scattering problem

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**Forward problem:** Given  $u_{\text{inc}} = \exp(ik\mathbf{x} \cdot \mathbf{d})$ , find  $u = u_s + u_{\text{inc}}$  such that

$$\begin{aligned} -\nabla^2 u - k^2 u &= 0 && \text{in } \mathbb{R}^2, \\ \nabla u \cdot \mathbf{n} &= 0 && \text{on the scatterer(s) surface,} \\ \lim_{r \rightarrow \infty} r^{1/2} \left( \frac{\partial u_s}{\partial r} - ik u_s \right) &= 0 && \text{Sommerfeld condition.} \end{aligned}$$

**Equivalent weak form:** Find  $u$  such that

$$a(\Omega; w, u) = \ell(\Omega; w) \quad \forall w.$$

# Introduction: Inverse scattering problem

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## Solution methods

- Backpropagation algorithm (Devaney, 1982).
  - + Fast.
  - Based on the Born or Rytov approximations.
- Nonlinear methods (Chew and Wang, 1990; Kleinman and van den Berg, 1992; Natterer and Wübbeling, 1995).
  - + Avoid Born or Rytov approximations.
  - Slow: methods are iterative in nature.

**Goal:** Construct an **efficient** algorithm that **avoids** these approximations.

## Propose two algorithms:

1. Based on the concept of an “optimal shape” for the inverse problem.
2. Improved algorithm based on the “optimal topology” for the inverse problem.

# First method: Shape optimization

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**Iterative method:** Find  $\Omega$  that minimizes

$$j(\Omega) = J(\Omega, u) = \frac{1}{2} \int_{\Gamma_s} \|u - u_m\|^2 d\Gamma$$

subject to the constraint

$$a(\Omega; w, u) = \ell(\Omega; w) \quad \forall w.$$

- **Optimization problem** with  $\Omega$  as the design variable.
- Use **gradient-based** algorithms to solve it.

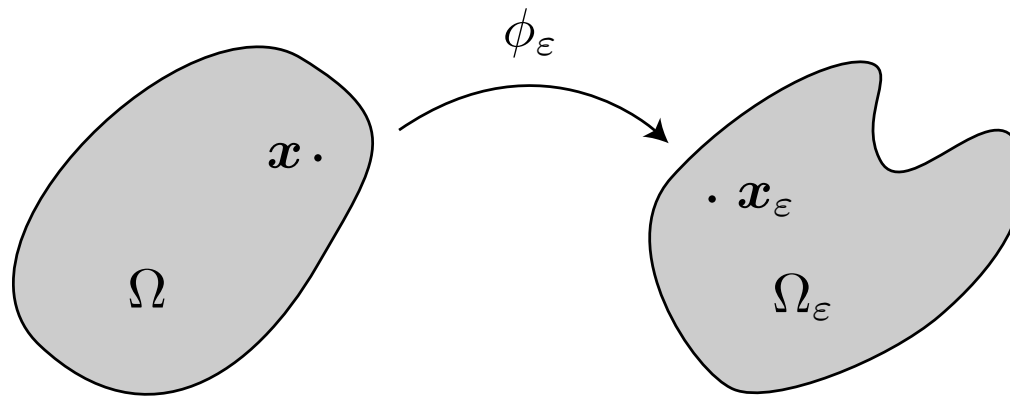
**Need to address the following issues:**

1. Differentiation with respect to  $\Omega$  (**shape differentiation**).
2. How to calculate derivatives in the presence of constraints given by variational equations?

# Shape differentiation

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## Derivative of $j(\Omega)$ in the $V$ -direction



Given the mapping

$$\begin{aligned}\phi_\epsilon &: \Omega \subset \mathbb{R}^2 \rightarrow \Omega_\epsilon \subset \mathbb{R}^2 \\ \phi_\epsilon(\mathbf{x}) &= \mathbf{x} + \epsilon \mathbf{V}(\mathbf{x}) \quad \forall \mathbf{x} \in \Omega,\end{aligned}$$

the **shape derivative** is

$$Dj(\Omega) \cdot \mathbf{V} = \left. \frac{d}{d\epsilon} j(\phi_\epsilon(\Omega)) \right|_{\epsilon=0}.$$



# Differentiation in the presence of constraints

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We want to calculate

$$Dj(\Omega) \cdot V = \left. \frac{d}{d\varepsilon} J(\Omega_\varepsilon, u_\varepsilon) \right|_{\varepsilon=0},$$

where  $u_\varepsilon$  satisfies

$$a(\Omega_\varepsilon; w, u_\varepsilon) = \ell(\Omega_\varepsilon; w) \quad \forall w.$$

Want to avoid computing  $\dot{u}_\varepsilon$ . For that, introduce the Lagrangian

$$\mathcal{L}(\Omega_\varepsilon, u_\varepsilon, \lambda) = J(\Omega_\varepsilon, u_\varepsilon) + \operatorname{Re}\left(a(\Omega_\varepsilon; \lambda, u_\varepsilon) - \ell(\Omega_\varepsilon; \lambda)\right).$$

So

$$\mathcal{L}(\Omega_\varepsilon, u_\varepsilon, \lambda) = J(\Omega_\varepsilon, u_\varepsilon) \quad \forall \lambda.$$

As a consequence,

$$Dj(\Omega) \cdot V = \left. \frac{d}{d\varepsilon} J(\Omega_\varepsilon, u_\varepsilon) \right|_{\varepsilon=0} = \left. \frac{d}{d\varepsilon} \mathcal{L}(\Omega_\varepsilon, u_\varepsilon, \lambda) \right|_{\varepsilon=0} \quad \forall \lambda.$$

Seems we did not get much, but...

# Differentiation in the presence of constraints

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**Differentiating the Lagrangian with respect to  $\varepsilon$  gives**

$$\begin{aligned}\frac{d}{d\varepsilon}\mathcal{L}(\Omega_\varepsilon, u_\varepsilon, \lambda) &= D_1J(\Omega_\varepsilon, u_\varepsilon) + \operatorname{Re}\left(D_1a(\Omega_\varepsilon; \lambda, u_\varepsilon) \cdot \mathbf{V} - D_1\ell(\Omega_\varepsilon; \lambda) \cdot \mathbf{V}\right) \\ &\quad + \operatorname{Re}(a(\Omega_\varepsilon; \lambda, \dot{u}_\varepsilon)) + D_2J(\Omega_\varepsilon, u_\varepsilon) \cdot \dot{u}_\varepsilon\end{aligned}$$

**Select  $\lambda$  that solves the adjoint equation**

$$\operatorname{Re}(a(\Omega_\varepsilon; \lambda, w)) + D_2J(\Omega_\varepsilon, u_\varepsilon) \cdot w = 0 \quad \forall w.$$

**Then**

$$\begin{aligned}Dj(\Omega) \cdot \mathbf{V} &= \left. \frac{d}{d\varepsilon}\mathcal{L}(\Omega_\varepsilon, u_\varepsilon, \lambda) \right|_{\varepsilon=0} \\ &= D_1J(\Omega, u) + \operatorname{Re}\left(D_1a(\Omega; \lambda, u) \cdot \mathbf{V} - D_1\ell(\Omega, \lambda) \cdot \mathbf{V}\right) \\ &= G(\Omega, u, \lambda, \mathbf{V}).\end{aligned}$$

# Differentiation in the presence of constraints

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**Summary.** To compute  $Dj(\Omega) \cdot V$

- Solve the forward problem: Find  $u$  such that

$$a(\Omega; w, u) = \ell(w) \quad \forall w.$$

- Solve the adjoint problem: Find  $\lambda$  such that

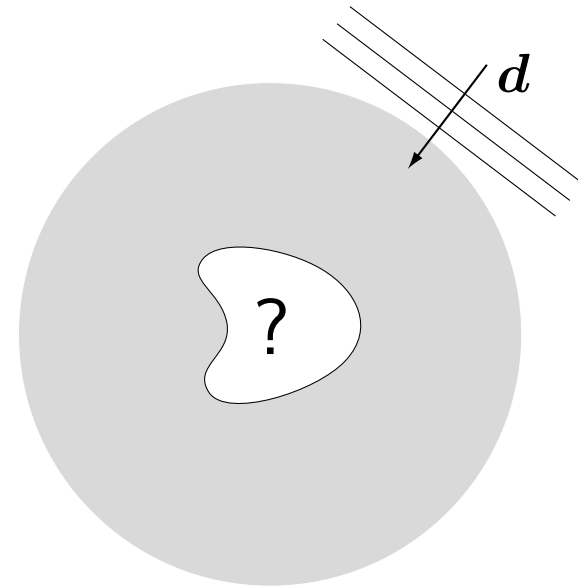
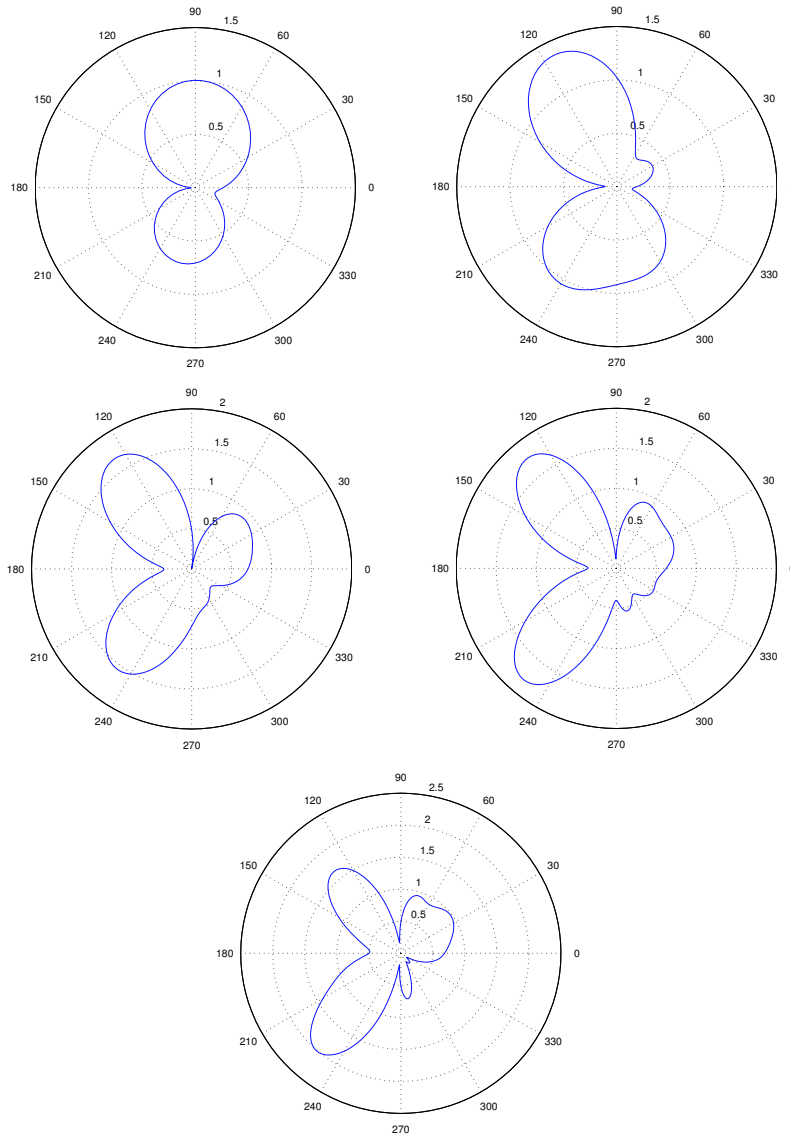
$$a(\Omega; w, \lambda^*) = -(w, (u - u_m)^*)_{\Gamma_s} \quad \forall w.$$

- Compute the shape derivative

$$Dj(\Omega) \cdot V = G(\Omega, u, \lambda, V).$$

# Reconstructions using shape optimization

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# Reconstructions using shape optimization

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# Reconstructions using shape optimization

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# Search for an improved method

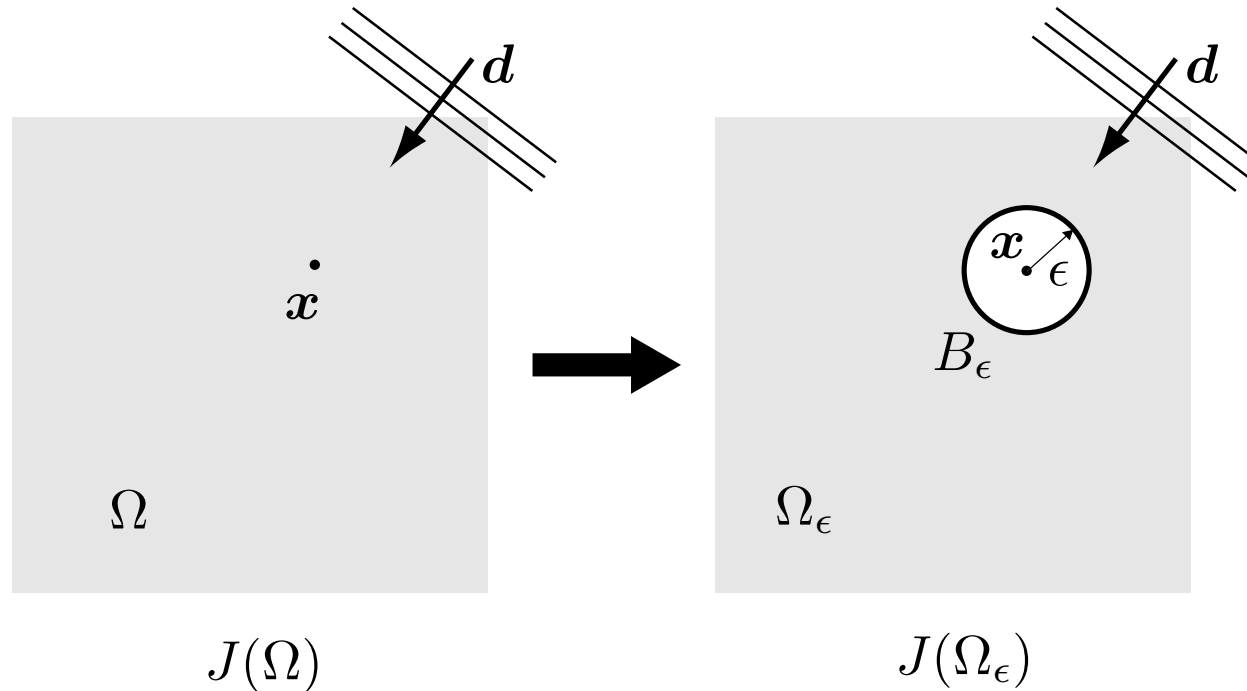
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## Criticisms to the previous method

- A-priori information (number of scatterers) is needed.
- Robustness problems.
- Method is iterative.

# Search for an improved method

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What if we could calculate the **scalar field**  $D_T(x)$  such that

$$J(\Omega_\epsilon) = J(\Omega) + D_T(x)f(\epsilon) + o(f(\epsilon))$$

$D_T(x)$  can be used as an **indicator** for the position (and shape) of scatterers in the domain  $\Omega$ .



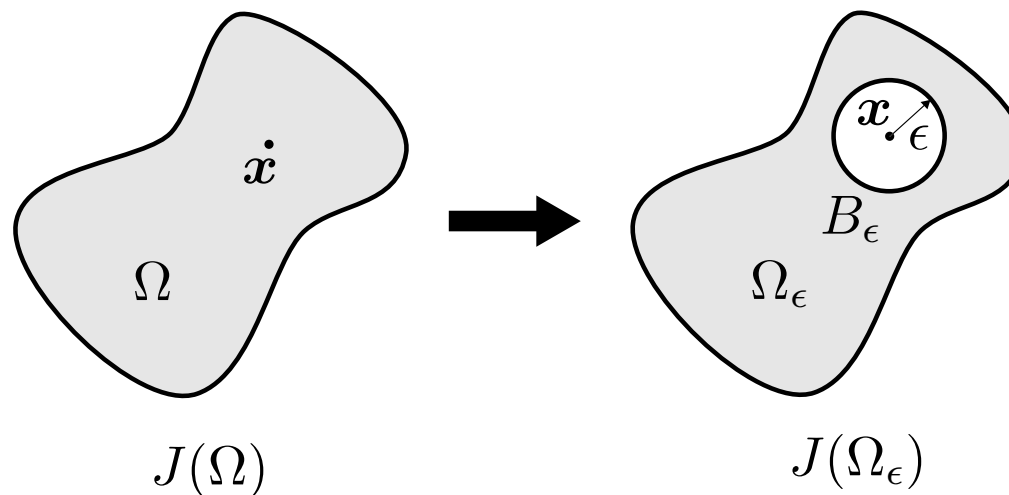
# Search for an improved method

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**Topological Derivative** [Sokolowski, 1999; Masmoudi, 1998]:

$$D_T(\mathbf{x}) := \lim_{\epsilon \rightarrow 0} \frac{J(\Omega_\epsilon) - J(\Omega)}{f(\epsilon)},$$

where  $\Omega_\epsilon = \Omega \setminus B_\epsilon(\mathbf{x})$ ,  $f(\epsilon)$  is a negative function that decreases monotonically and  $f(\epsilon) \rightarrow 0$  as  $\epsilon \rightarrow 0^+$ .

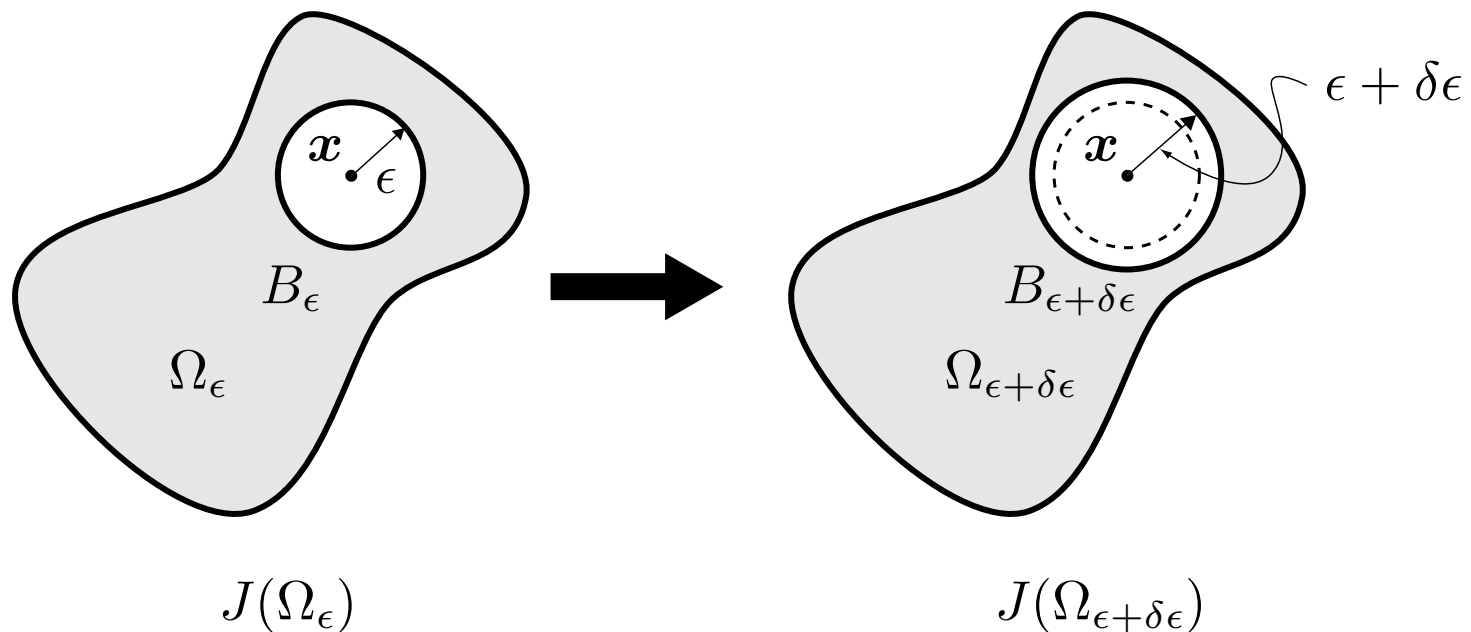


# Search for an improved method

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Instead, we can define the topological derivative as follows

$$D_T^1(\mathbf{x}) = \lim_{\epsilon \rightarrow 0} \left\{ \lim_{\delta \epsilon \rightarrow 0} \frac{J(\Omega_{\epsilon+\delta\epsilon}) - J(\Omega_{\epsilon})}{f(\epsilon + \delta\epsilon) - f(\epsilon)} \right\}.$$



# Search for an improved method

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Define:

$$\begin{aligned}\Omega_\tau &= \{\mathbf{x}_\tau \in \mathbb{R}^n \mid \exists \mathbf{x} \in \Omega_\epsilon, \mathbf{x}_\tau = \mathbf{x} + \tau \mathbf{V}\}, \\ \mathbf{V} &= \begin{cases} V_n \mathbf{n} & V_n < 0 \text{ constant on } \partial B_\epsilon, \\ \mathbf{0} & \text{on } \partial\Omega. \end{cases}\end{aligned}$$

**Theorem:**

$$D_T(\mathbf{x}) = D_T^1(\mathbf{x}) = \lim_{\epsilon \rightarrow 0} \frac{1}{f'(\epsilon)|V_n|} \underbrace{\frac{d}{d\tau} J(\Omega_\tau) \Big|_{\tau=0}}_{(\bullet)}$$

for  $f(\epsilon)$  such that  $0 < |D_T(\mathbf{x})| < \infty$ .

**Remark:**  $(\bullet)$  is the shape derivative!

## Second method: Topological derivative

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In our case

$$D_T(\boldsymbol{x}) = \operatorname{Re} \left[ \nabla \lambda^*(\boldsymbol{x}) \cdot \nabla u(\boldsymbol{x}) - k^2 \lambda^*(\boldsymbol{x}) u(\boldsymbol{x}) \right] .$$

Both  $u$  and  $\lambda$  can be calculated analytically!

$$\begin{aligned} u(\boldsymbol{x}) &= u_{\text{inc}}(\boldsymbol{x}) = \exp(\mathrm{i}k\boldsymbol{x} \cdot \boldsymbol{d}) \\ \lambda(\boldsymbol{x}(r, \theta)) &= \sum_n A_n J_{|n|}(kr) \exp(\mathrm{i}n\theta) \\ A_n &= f_n(\text{Fourier components of measured signature}) \end{aligned}$$

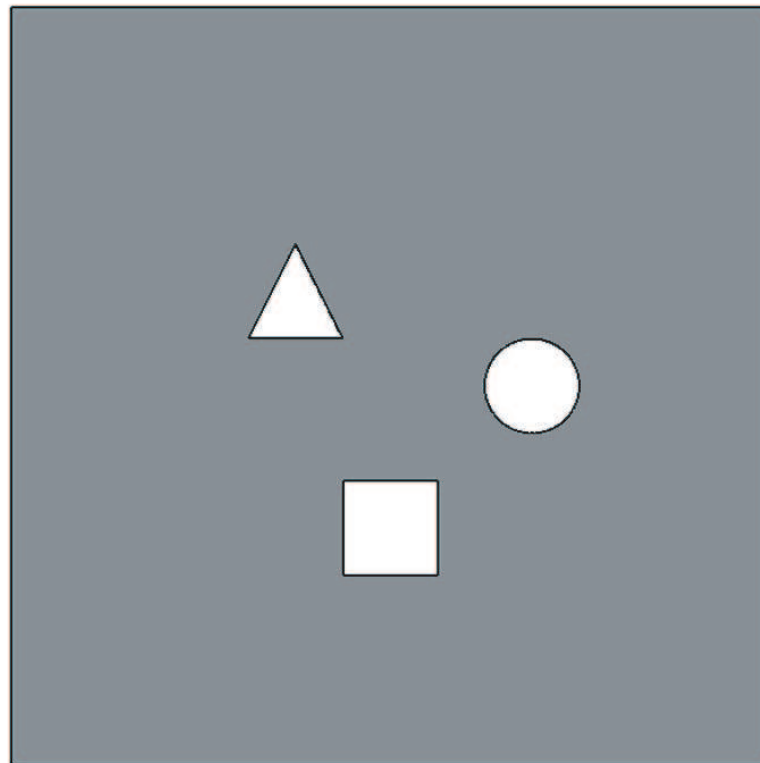
### Method:

Plot  $D_T(\boldsymbol{x})$ ,  $\boldsymbol{x} \in \Omega$  and look for points where  $D_T(\boldsymbol{x})$  attains large values.

# Reconstructions using topological derivative

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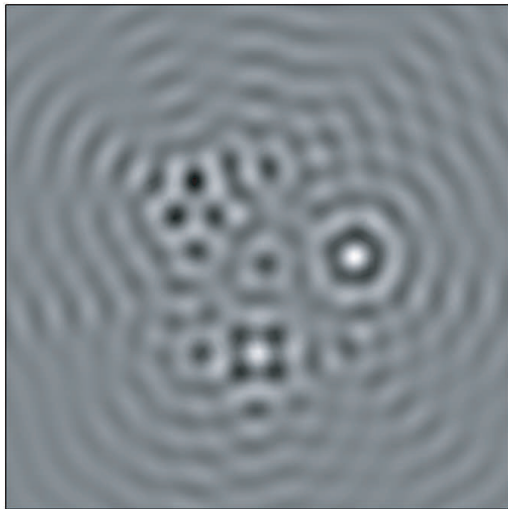
Target



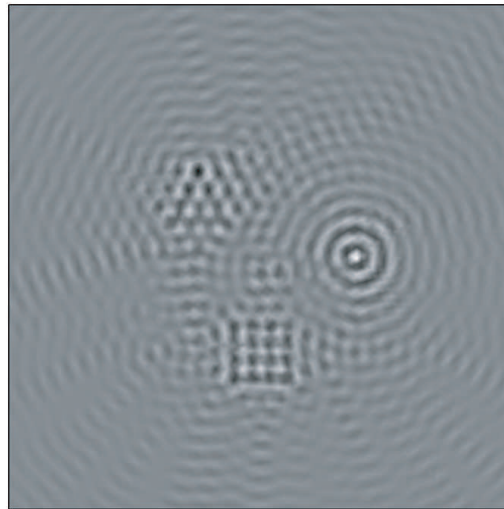
# Reconstructions using topological derivative

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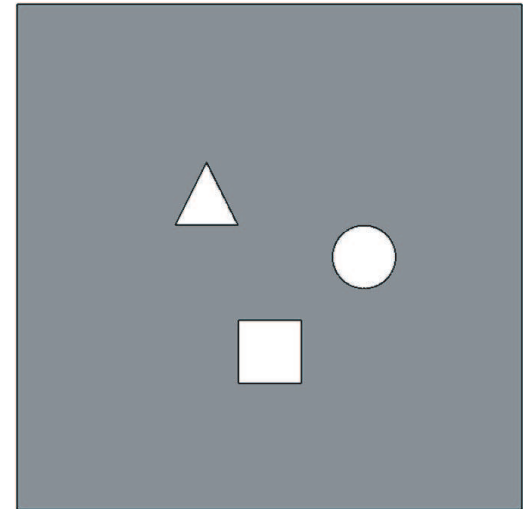
Topological derivatives for  $n_{\text{iw}} = n_{\text{dp}} = 120$ .



$k = 6$



$k = 12$

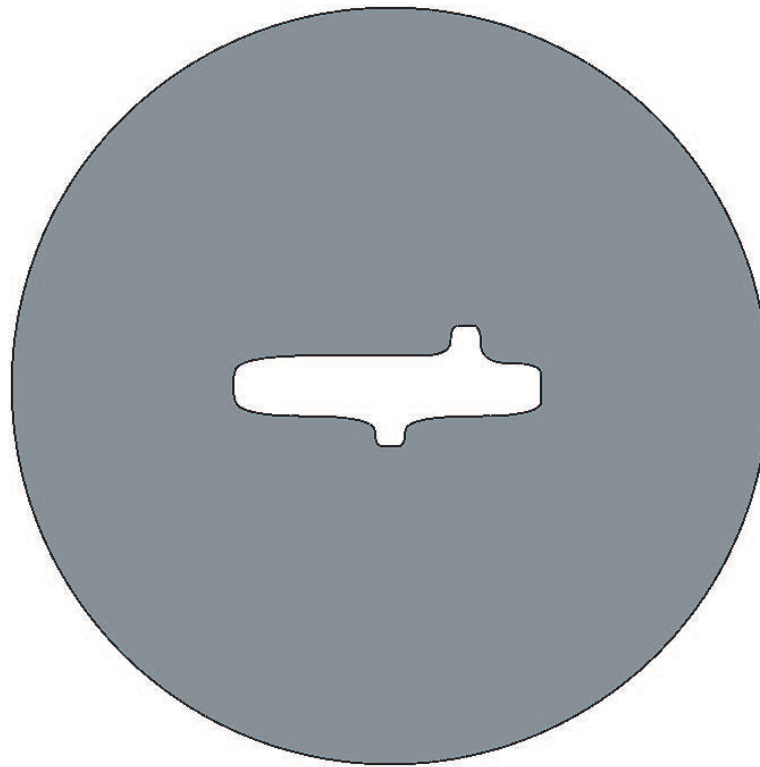


Target

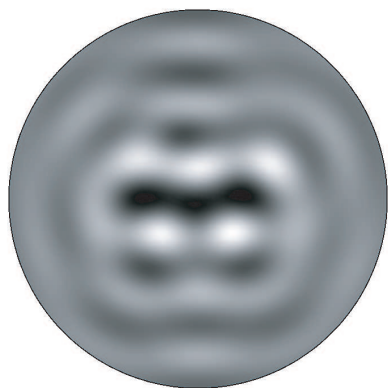
# Reconstructions using topological derivative

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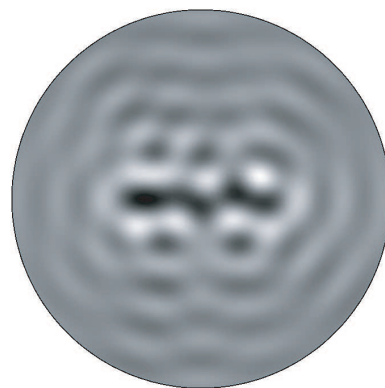
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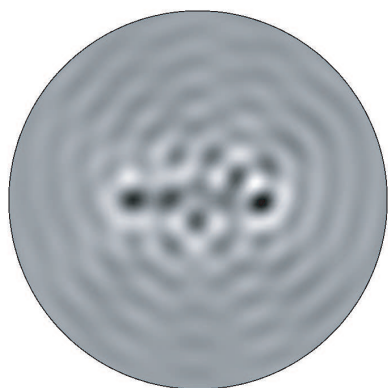
Topological derivatives for  $n_{\text{iw}} = n_{\text{dp}} = 120$ .



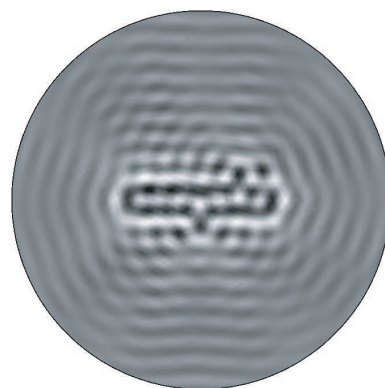
$k = 2$



$k = 3$



$k = 4$



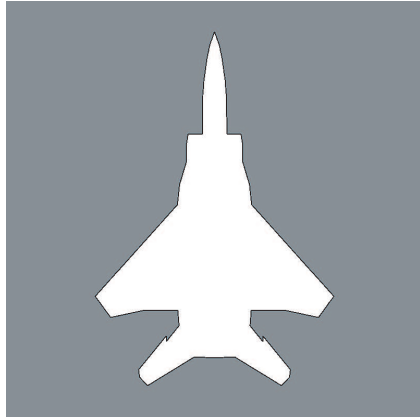
$k = 6$



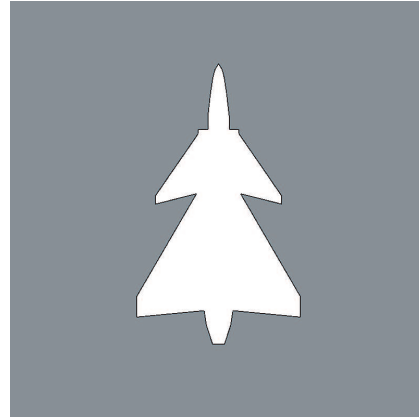
# Reconstructions using topological derivative

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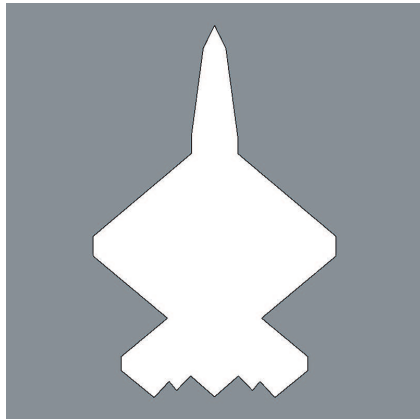
## Targets



F15



VFY218



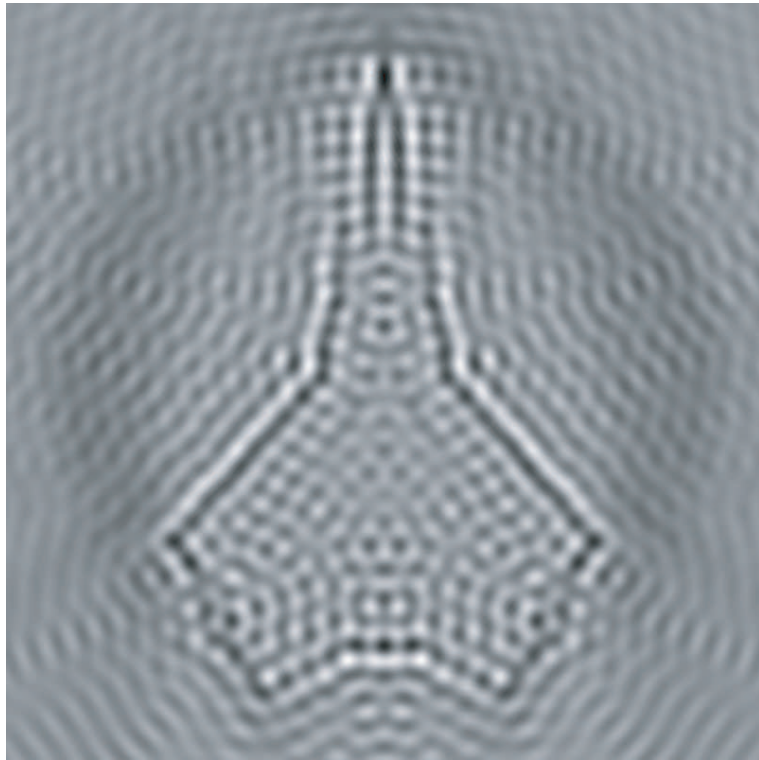
YF23



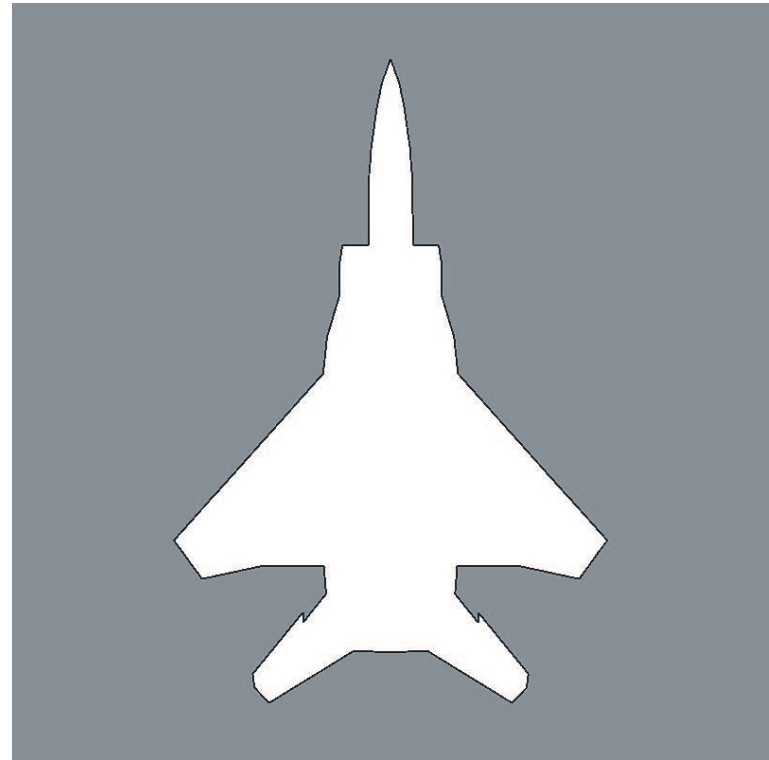
B2

# Reconstructions using topological derivative

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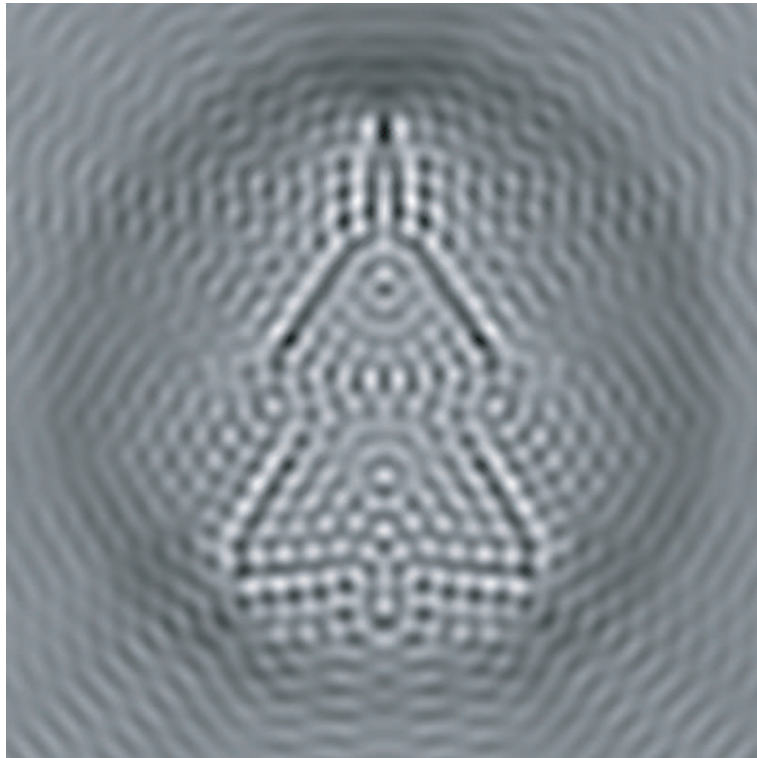
$\nu = 200\text{MHz}$



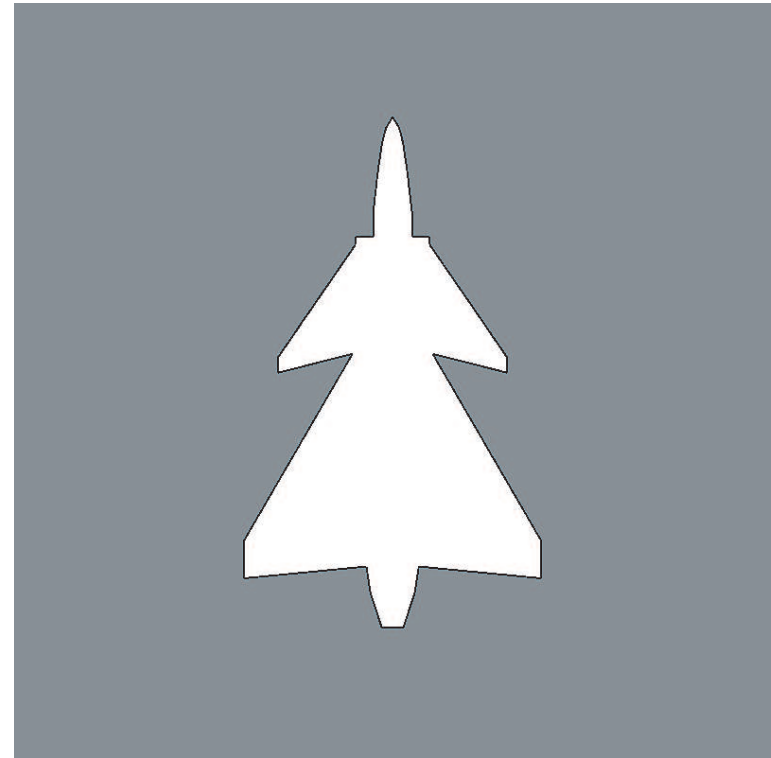
Target

# Reconstructions using topological derivative

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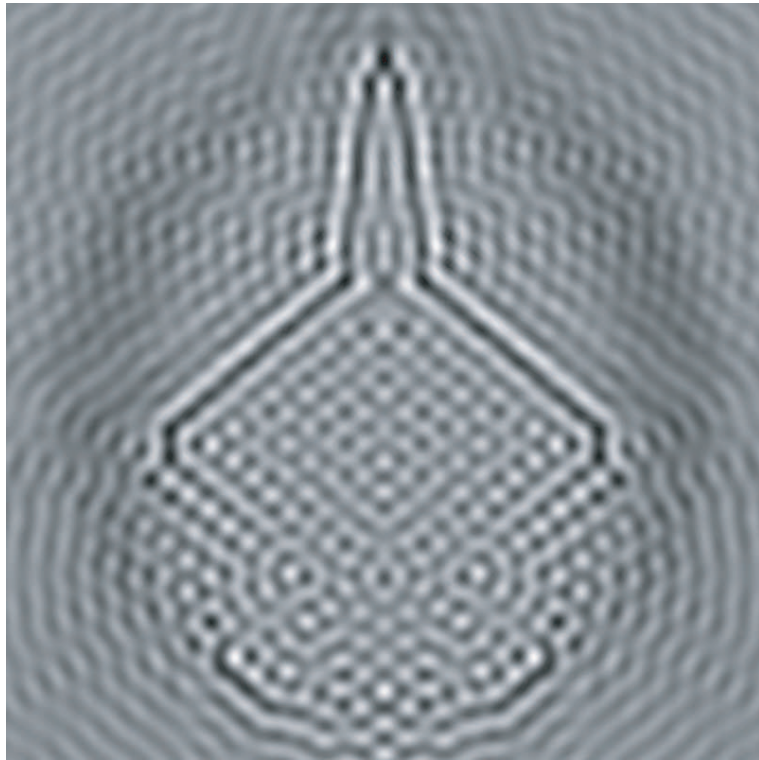
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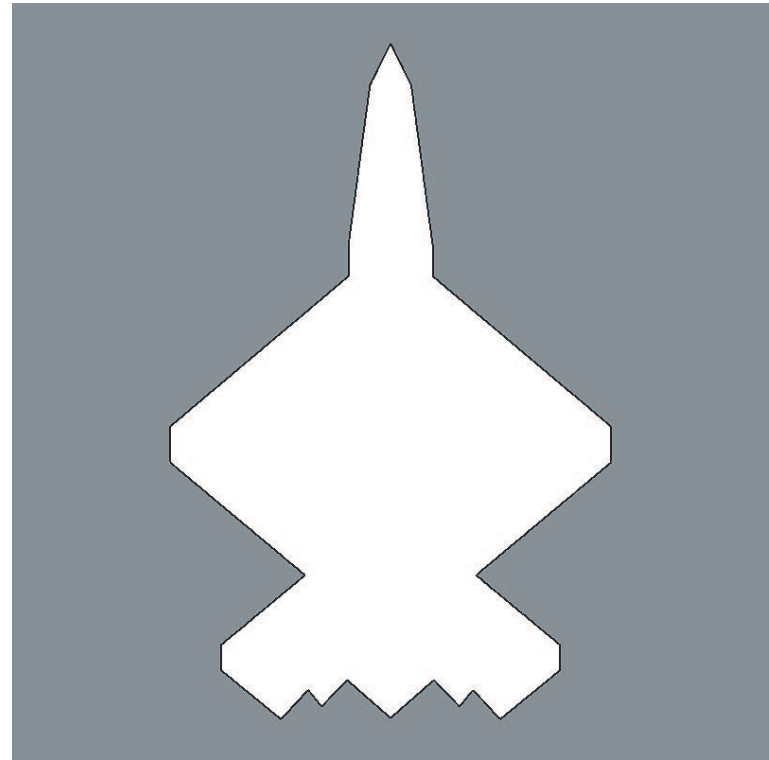
Target

# Reconstructions using topological derivative

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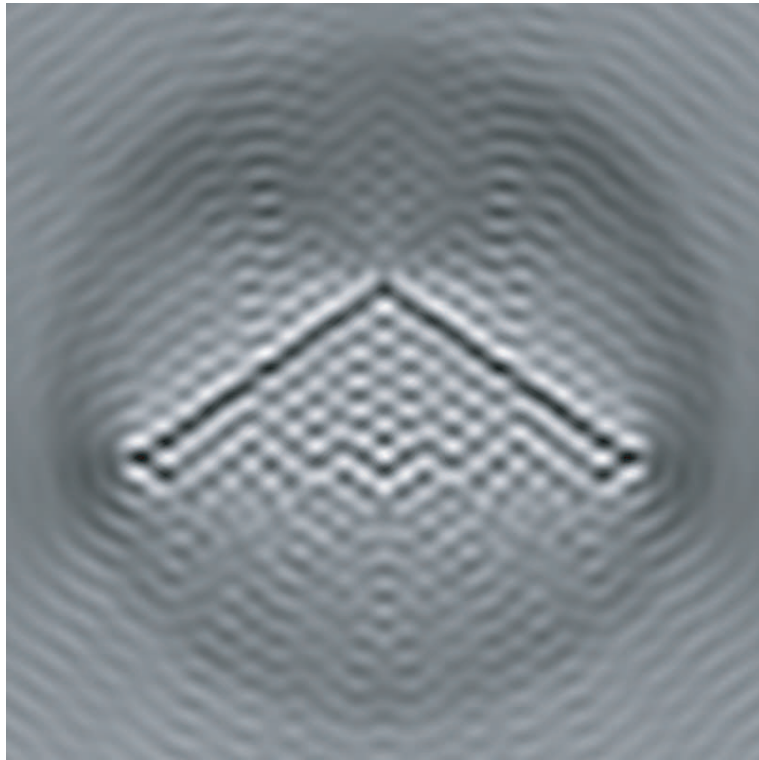
$\nu = 200\text{MHz}$



Target

# Reconstructions using topological derivative

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$\nu = 200\text{MHz}$



Target

## Conclusions and future work

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Shape sensitivity analysis/topological derivative can be used as a tool to solve inverse scattering problems.

Comparison with other approaches.

3D reconstructions.

Reconstruction of refractive index.

Seismic imaging.

**Work with real data!**